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The Health Effects of Medicare for the Near-Elderly Uninsured
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ABSTRACT

We study how the trajectory of health for the near-elderly uninsured changes upon enrolling into Medicare at the age of 65. We find that Medicare increases the probability of the previously uninsured having excellent or very good health, decreases their probability of being in good health, and has no discernable effects at lower health levels. Surprisingly, we found Medicare had a similar effect on health for the previously insured. This suggests that Medicare helps the relatively healthy 65 year olds, but does little for those who are already in declining health once they reach the age of 65. The improvement in health between the uninsured and insured were not statistically different from each other. The stability of insurance coverage afforded by Medicare may be the source of the health benefit suggesting that universal coverage at other ages may have similar health effects.

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I. Introduction

The Medicare program provides near universal health insurance coverage for Americans over the age of 65, while those under 65 are predominantly reliant on employer-sponsored health insurance for affordable health insurance coverage. The substantial gaps in coverage resulting from the employer-based system are partially filled by individually purchased policies and public insurance (primarily Medicaid), but 18% of the non-elderly, 45.5 million people in 2004, remain without health insurance. Because health insurance reduces the financial barriers of using the medical system to maintain or prevent the deterioration of health, the uninsured may experience indirect negative consequences to their health as a result of health care foregone from a lack of incentives for obtaining medical care (Institute of Medicine, 2001). Because the near-elderly uninsured obtain health insurance through the Medicare program at the age of 65, they may experience a health benefit from this transition. The goal of this paper is to determine the effect of the Medicare program on the health of the near-elderly uninsured.

Understanding whether there is a health benefit to the near-elderly uninsured from the Medicare program is an important aspect of policy debates regarding expanding and contracting Medicare coverage. As we approach the year 2018 -- when the Medicare trust fund reserves are projected to be exhausted (Trustees of the Social Security and Medicare trust funds, 2006) – policy changes to Medicare may become necessary. The near-elderly uninsured may be particularly vulnerable to any contraction in Medicare coverage because Medicare arrives at an age when treatable health conditions are emerging at an increasing rate. Despite the importance of health insurance for this age group, 25% of the near-elderly will experience a period without health insurance between ages 55 and 65 (Baker et al., 2005). This may be partially due to the fact that affordable coverage is difficult to find for those lacking health insurance with existing or emerging health conditions. Although all are guaranteed an issue of a health insurance policy in the individual market through the Health Insurance Portability and Accountability Act of 1996 (HIPAA), the law does not limit the amount insurers can charge for such coverage. Hence, premium levels can exceed the financial resources of all but the wealthiest individuals. As a result, several policy proposals have emerged to address this vulnerable group including expansions in the Medicare program to cover the uninsured in the 55 to 65 age group. Understanding the direct and indirect benefits of providing health insurance to the near-elderly uninsured can help inform these policies. The health effects of policies specifically aimed to provide insurance to the near-elderly uninsured have not been established.

In this paper, we use a quasi-experimental approach to establish the health effects of insurance for the near-elderly uninsured. Those who acquire health insurance typically do so for a reason: they may have gained employment that offers coverage; they may have qualified for coverage from the federal government as a result of poverty or disability; or they may have purchased insurance in the individual market. In all of these cases, the decision to purchase health insurance may be related to recent and projected changes in health status, making it difficult to empirically assess the health effects of acquiring insurance using cross-sectional comparisons. In contrast, uninsured persons who turn 65 acquire health insurance through the Medicare program simply by aging in. Therefore, by using panel data to assess how gaining Medicare coverage at age 65 changes the health trajectory of the near-elderly uninsured as they age into their late 60s and early 70s, we can identify how insurance changes the trajectory of health for this group.

II. Literature on Health Insurance and Health

The Institute of Medicine Committee on the Consequences of Uninsurance examined the relationship between being uninsured and the health of American adults (Institute of Medicine, 2002). The Committee concluded that if the roughly 30 million working-age uninsured Americans were to become continuously insured, their health would be expected to improve. The studies on general health supporting these conclusions find that being uninsured for relatively short periods (1 to 4 years) appears to result in a decrease in general health status (Baker et al., 2001) and that uninsured adults followed for 5 to 17 years are at higher risk of premature death than are persons with private coverage (Franks et al., 1993; Sorlie et al., 1994). Hundreds of other studies have also documented a disparity in morbidity between the uninsured and the insured (Literature reviews: Brown et al., 1998; Hadley, 2003; Institute of Medicine, 2002). From these studies, however, it is difficult to determine the causal relation between health insurance and health for several reasons. A positive association between health insurance and health may reflect the effects of health on health insurance (reverse causation) or the effects of some other unobserved attribute on both health insurance and health (selection) (Levy and Meltzer, 2004).

The only experimental study of the effect of insurance on health was the RAND Health Insurance Experiment (HIE). Between 1974 and 1982, the HIE randomly assigned roughly 2,000 families to one of 14 experimental health plans that varied in their cost-sharing arrangements (Newhouse et al., 1981; Newhouse et al., 1993). Although the study found sizable effects of more generous health insurance on use and expenditures, effects on health status were more modest. For low-income persons with high blood pressure, free care brought an improvement in blood pressure control. Vision also improved among those with poor vision. No significant effects were detected on eight other measures of health status and health habits for adults (Brook et al., 1983). The absence of a health effect could be due to the presence of a cap on out-of-pocket health expenditures by all enrollees that was, at most, 15% of income (Newhouse et al., 1993). This randomized social experiment is of limited use for our purposes because (1) it did not include a study group with no health insurance; (2) it excluded the Medicare-eligible population and thus excluded the elderly population; and (3) the health care delivery system and medicine have both changed substantially since the mid to late seventies.

By exploiting a natural experiment from a change in the eligibility of pregnant women for Medicaid benefits, a few quasi-experimental studies have provided evidence of a causal relation between health insurance and health of newborns (Joyce, 1998; Epstein and Newhouse, 1998; Baldwin et al., 1998; Ray et al., 1997; Currie and Gruber, 1996a, 1996b, 1997; Reichman and Florio, 1995; Haas et al., 1993; Fossett et al., 1992; Buescher et al., 1991; Piper et al., 1990). The findings generally suggest that health insurance does result in modest reductions in infant mortality.

More recently, quasi-experimental designs have been applied to the question of health and health insurance around the introduction of Medicare. Decker and Rapaport (2002) found that mortality decreased significantly after women diagnosed with early breast cancer acquired Medicare. Finkelstein and McKnight (2005) reported that the establishment of Medicare in 1965 had no discernible impact on the mortality of the elderly in the 10 years following Medicare's enactment.

The hypothesized mechanism by which health effects might occur is through increased or more timely use of medical services with insurance and Medicare. The HIE provides direct experimental evidence that a reduction in out-of-pocket costs increases utilization and expenditures for health care services (Manning et al., 1987; Newhouse et al., 1993). Several recent observational studies provide strong evidence of the increased use of medical services due to Medicare. State hospital discharge datasets have also been used to assess how Medicare might alter medical service use (Lichtenberg, 2002; Card et al., 2004). These studies have found that utilization rates for doctor visits and hospitalizations (particularly hospitalizations for discretionary conditions) increase at age 65, the cusp of Medicare eligibility. McWilliams et al. (2003), using the Health and Retirement Study (HRS), found a jump in preventive care utilization between just before and just after age 65. Because so many medical procedures have been found to reduce risks of death and disability (Aiken and Bays, 1984; Cassel et al., 1999; Fuchs, 1999; McClellan and Noguchi, 1998), the assertion that Medicare and other forms of health insurance that improved access to medical care has helped Americans live longer, healthier, and more independent lives is compelling.

Yet no study has looked directly at how the introduction of Medicare may change the health trajectory of the previously uninsured using individual-level data. We hypothesize that the health trajectory of previously uninsured persons will improve as a result of the introduction of Medicare at age 65. The mechanism for this change would be the greater use of medical care induced by subsidized, universal health insurance coverage. There may also be contemporaneous changes occurring at this age. The most obvious are the higher rates of retirement and the introduction of Social Security payments at age 65. Because of these other changes occurring simultaneously, we will also test whether the health trajectory of the previously uninsured changes by more than that of the previously insured.

III. Conceptual and Empirical Framework

Health insurance and medical care exist to maintain and improve health, and to guard against the financial risks associated with poor health. Health can be viewed as an asset that has a natural rate of deterioration over time. A medical event can hasten that deterioration. Medical care is used after a medical event to restore, maintain, or prevent further decline in health (Grossman, 1972). The expenditure for this medical care is sometimes large and unexpected. Insurance reduces the financial risk associated with higher medical expenses after a health event. Health insurance plays other important roles in this relationship, including allowing access to health care that would otherwise be unaffordable (de Meza 1983, Nyman, 1999) and increasing demand for medical care because the person using health care with insurance typically does not pay the entire cost of that care (Pauly, 1968).

Determining whether the additional medical care afforded by the introduction of health insurance affects health may be complicated by adverse selection: the decision to acquire or to drop health insurance is often related to one's health status (sometimes this is not a decision – it happens because a person involuntarily loses their job with employment-based benefits). For example, one could acquire health insurance before seeing the doctor for an emerging health problem. Unless the health status factors that led to the change in insurance status are perfectly controlled for, assessing causality in the empirical evaluation of the relationship between change in health insurance status and health status is problematic because the effects of the unmeasured or mismeasured aspects of poor health may be attributed to being insured.

The empirical framework in this paper focuses on the introduction of Medicare insurance at age 65, where the introduction of government-subsidized health insurance for previously uninsured persons occurs independently of any underlying health status change other than aging one more year. Because government policy restricts entry into Medicare until age 65 for most Americans, those who take up Medicare insurance (at age 65, but not those before age 65) do so for reasons other than changes in health status. It is the introduction of health insurance at age 65 for no other reason than turning this age that creates the natural experiment used in our key comparisons.

A stylized version of our model is expressed as

$$\Delta H = \beta_0 + \beta_1 U + \beta_2 M + \beta_3 U * M + \beta_4 Age$$

where ΔH is the change in health status between age and age+2, U is an indicator of whether the subject is uninsured prior to age 65, M is an indicator for the age the subjects is enrolled in Medicare. We can determine from the estimated coefficients the average change in health status

($\overline{\Delta H}$) in the pre-Medicare and post-Medicare period for both the Uninsured and the Insured groups: $\Delta H_{Upre}=\beta_0+\beta_1$, $\Delta H_{Upost}=\beta_0+\beta_1+\beta_2+\beta_3$, $\Delta H_{Ipre}=\beta_0$, and $\Delta H_{Ipost}=\beta_0+\beta_2$. To simplify the notation, we refer to these four $\overline{\Delta H}$ groups as U_{pre}, U_{post}, I_{pre}, and I_{post}. They are depicted as slopes in Figure 1. From $\overline{\Delta H}$, we can estimate the change in the rate of health decline after the introduction of Medicare for the Uninsured and Insured groups (ΔU and ΔI, respectively) by subtracting the pre change from the post change (i.e. $\Delta U= U_{post}-U_{pre}$; $\Delta I= I_{post}-I_{pre}$). Finally, we estimate the change in the rate of health decline for the Uninsured using the Insured group as a control by $\Delta U-\Delta I$. Note that while, for simplicity, the graph depicts no intercept change at 65, our modeling does allow for this.

This experimental opportunity at age 65 is not exact for two reasons. First, initial insurance status is not randomly assigned, which could bias our findings: certain factors, such as low socioeconomic status, can cause poor health and lower rates of health insurance coverage. With the first-difference approach, baseline health differences between the insured and uninsured (both observed and unobserved differences) are removed. By controlling for the characteristics of the groups, we control for differences in the rate of change in health status due to differences in these characteristics. Second, other changes confounded with health status may also occur at age 65, including retirement and Social Security payments. We consider the change in trajectory of the insured as a proxy for these and other contemporaneous changes. We also directly consider how sensitive our comparisons are to the time-dependent (but potentially endogenous) retirement status and Social Security payments.

IV. Data

The data were obtained from the original age-eligible cohort of the Health and Retirement Study (HRS). The HRS began in 1992 as a national longitudinal study of the noninstitutionalized population born between 1931 and 1941 (i.e., persons age 51 to 61 at the time of the baseline survey) and their spouses. Respondents and their spouses have been reinterviewed every 2 years since. The investigators used a complex sample design in which black persons, Hispanic persons, and residents of Florida were oversampled. The initial age-eligible sample was 9,771. We use all biannual waves from 1992 to 2004. Figure 2 describes the aging of the original sample at each wave.

Our study sample includes birth cohorts 1932-1937 (grey shading in Figure 2). These birth cohorts have the potential to be observed at age 59/60 and then being observed at least twice upon reaching the age of 65. By using the same participants for the pre- and post-eligibility periods removes the possibility of a birth cohort effect; we excluded the 1938-1941 birth cohorts for this reason. Starting all individuals when they are 59/60 removes the possibility of left-censoring bias that would result from a differential death rate by insurance status and age cohort; to avoid this, we excluded the 1931 cohort and started following the included birth cohorts at age 59/60. As a result, we studied the 1932-1937 birth cohorts (N = 5,086).

We also excluded persons who dropped out or died before age 59/60 (n = 226), those with missing insurance status (n = 55), the few persons who reported never receiving Medicare after age 65 (n = 31), those with no follow-up after age 59/60 (n = 127), and those on Medicare or Medicaid at age 59/60 (n = 572). We used sensitivity analysis to test the influence of this last exclusion. Our final study sample consists of 4,075 persons (Table 1).

In each wave, HRS respondents provided detailed information about their current insurance coverage. They were asked whether they received any employment-based coverage, individual coverage, and coverage through federal programs such as Medicare or Medicaid. The uninsured are defined as those whose response indicated they had no form of private or public insurance. Those uninsured at age 59/60 represent the uninsured group and those insured at age 59/60 represent the insured group. The insured group consists of 3,484 persons, and the uninsured group consists of 591 persons (Table 2). Everyone is insured through Medicare once they cross the age 65 threshold, but the analytical labels for our comparison groups are held fixed according to their insurance status at age 59/60. The percentage of uninsured persons drops from 14.5% to 14.0% between the pre and post period because of the higher death rate in the uninsured group.

However, switching between insured and uninsured states is possible before age 65. In fact, 9.7% of the sample switched from insured to uninsured or from uninsured to insured between 59/60 and 63/64. Because our interest is determining whether health is a consequence of one's insurance status, we would like the definition of insurance status to not be a consequence of a health event. Therefore, our primary analysis is based on the initial insurance status (i.e. insurance status at age 59/60). In a sensitivity analysis, we compare the group continuously insured and the group continuously uninsured.

While wave-specific overall response rates average 88.6%, persons who are uninsured are more likely to be lost to follow-up than persons who are insured. The HRS sample weights account for attrition (in addition to the complex sample design) through a post-stratification of the HRS to the Current Population Survey (CPS) by age, sex, race, ethnicity, and marital status groups. This stratification explains differential non-response over time by those major demographic groups. Because differential attrition by insurance status remained, we used the CPS to apply an additional adjustment to the HRS weights by age, race, labor force status, education, and insurance status to arrive at our final weights. The details of this adjustment are provided in the technical appendix. These adjusted weights are used in all analyses.

The primary outcome measure is self-reported health status combined with mortality. The former is measured by the question, "Would you say that your health is excellent, very good, good, fair, or poor?" Mortality is reported by surviving family members or other contacts, and non-reported mortality is obtained through a link of the HRS files with the National Death Index. Self-reported health status has been used as a measure of health for many previous studies that related insurance coverage to health outcomes (Fihn and Wicher, 1988; Hafner-Eaton, 1993; Lurie et al., 1984; Short and Lair, 1994) and has been shown to have predictive validity for both future health care utilization and subsequent mortality (Manning et al., 1987; DeSalvo, 2006). Due to the small sample sizes on the extremes of this scale, we combine the excellent and very good health into a single category, and the fair and poor categories into another category.

The primary control variables include sex, age, education, ethnicity, race, and region. Baseline marital status, income, and wealth and time-varying covariates of retirement status, receipt of Social Security payments, and marital status are included as explanatory variables in sensitivity analysis only because these variables may be considered endogenous. Wealth and income measures are converted to 2004 real U.S. dollars adjusted by the Consumer Price Index.

Retirement status is based on self-reported categories of not retired, fully retired, partially retired, or not applicable.

V. Empirical Model

We estimate health state transitions between health state at age *t* (H_t) and the health state at age *t+2* (H_{t+2}), one survey wave later. H_{t+2} is a categorical variable with four categories: j = (excellent/very good (E), good (G), fair/poor (F), and died (D)). The transitions from H_t to H_{t+2} are estimated by using the following multinomial logit model:

$$\ln\left[\frac{p_{ij}}{p_{iE}}\right] = \beta_{ij0} + \beta_{ij1}H_t + \beta_{ij2}U_t + \beta_{ij3}M_t + \beta_{ij4}H_t * U_t + \beta_{ij5}H_t * M_t + \beta_{ij6}M_t * U_t$$
$$+ \beta_{ij7}H_t * U_t * M_t + \beta_{ij8}Age_t + \beta_{ijn}X_n$$

where p_{ij} is the probability of being in health state category *j* for participant *i* at age *t+2* given his or her health and other characteristics: $p_{ij} = pr(H_{t+1} = j \mid H_t = i; age_t; X)$. A more traditional fixed effect model of health state would not be appropriate because death is one of the states and it is an absorbing state. While we considered an ordered logit specification for this model because our measure of health status is ordered, we abandoned this approach because of the poor performance of this model on the Brant test and the fact that the multinomial logit generally passed the revised Hosmer-Lemeshow test, while the ordered logit universally failed this test. (The details of our specification tests are provided in the technical appendix.)

To provide interpretability from the large number of estimated relevant coefficients in our multinomial logit model, we simulate how the estimated health transitions will change health for U and I as the subjects in these groups age. The simulation is conducted as follows. First, we start with the sample when they are 59/60. We then use the estimated coefficients from the health transition model to predict their probability of being in each of the four health states at 61/62. Each subject's realized health state at 61/62 is then determined from a random draw from a uniform distribution on the unit interval. We then repeat this process using the predicted health states at 61/62 as their baseline health state for the prediction of the probability of being in each of the four health states at 63/64. This process is repeated until each subject is aged to 71/72. Those subjects who enter the dead state are treated as dead for all remaining ages in the simulation and are dropped from the repeated predictions for subsequent ages. In addition to simulating the health of subjects as they age onto Medicare, we simulate the health of subjects as they age from 65 to 71 assuming they did not receive Medicare. This out-of-sample simulation is performed by not "turning on M" for ages beyond 65.

The simulation is similar to a Markov chain, but instead of using average transition probabilities and averages for initial conditions, the Markov process is conducted at the individual level. This allows for unique transition probabilities for each individual's covariates. This greatly simplifies the process when the time dependent covariates of retirement status and Social Security payments are added to the model. However, random variation enters because realized states are based on a random draw. This variation is reduced because we repeat the simulation 100 times for each individual.

When the simulation is complete, the average proportion of subjects in each health state at each age for each insurance group is estimated as well as for the counterfactual post period of U and I. We then estimate the change in health state over a 6-year period for each insurance group (i.e. U_{pre}, I_{pre}, U_{post}, I_{post}) by subtracting the health state probability at age 71 from the health state probability at age 65. The difference-in-difference for each insurance group (ΔU and ΔI) is defined as the difference in a 6-year change in health state caused by Medicare enrollment at age 65 (($U_{post} - U_{pre}$) and ($I_{post} - I_{pre}$)). Finally, the difference between these two differences gives the change in health status caused by Medicare enrollment at age 65 for the uninsured, controlling for any contemporaneous changes in health over time. These calculations are depicted graphically in Figure 3.

We estimated standard errors and significance in the multinomial logit using robust standard errors (White, 1980), correcting for clustering at the person level. We estimated confidence intervals of the health state probabilities estimated in the simulation using the percentile method from a non-parametric clustered bootstrap. The cluster was at the individual level to maintain the serial correlation pattern at the individual level without assuming an explicit form for the autocorrelation (Efron and Tibshirani, 1993).

We then estimate the base model for several important subgroups: continuous insurance groups, by gender, for low income and low wealth, and for those with and without supplemental insurance. Low income (wealth) group is defined as those with income (wealth) below the median in that wave when 59/60. For the 1996 wave, this translates into income below $46,000 and wealth below $156,000 in 2000 dollars. Supplemental insurance is defined as any additional insurance to Medicare. This includes employer-sponsored insurance, individual insurance, a MediGap plan, VA Champus, and Medicaid. Finally, we perform several robustness checks. We explore whether the results are robust to additional control variables such as time-dependent labor force participation and Social Security payments, to alternative age specifications, to alternative health status categorizations, and to weighting.

VI. Results

Table 3 shows the baseline characteristics of the study sample by insurance status. The insured and uninsured groups in the HRS at age 59/60 are representative of these groups in the United States. The uninsured are more likely to be in fair or poor health, are less likely to work, have lower education and lower income, and are more likely to be African American or Hispanic. Although the uninsured are more likely to have diabetes and psychiatric problems and to visit the hospital, they are less likely to visit the doctor.

Table 4 shows the coefficients of the multinomial regression coefficients, with the excellent/very good group being treated as the reference category. The tests of significance for key groups of variables are displayed at the bottom of the table. Here we see that the health of the uninsured is different from that of the insured in the pre-and post-Medicare periods. The health status differences before and after Medicare within insurance group approaches significance at the .05 level. The difference in the rates of change pre- vs. post-Medicare between the uninsured and insured is not statistically significant.

To better understand the direction of these health changes, we turn to the simulated trajectories depicted in Figure 4. In the northwest quadrant we see the trajectory for the excellent/very good health status. The darker lines represent the uninsured group trajectory and the lighter lines represent the insured group trajectory. The uninsured trajectory is below the insured trajectory representing their inferior health. Both lines decline with age representing deteriorating health with age and the monotonically increasing probability of being in the dead health state. At age 65 there is a kink in the trajectories which represents the change in the rate of health decline post Medicare enrollment. The dashed line is the pre-65 trajectory, based on the pre-65 transition probabilities, extended into the post-65 ages. The divergence between the two lines for each insurance group represents the effect of Medicare on that insurance group. Here we see the increase in the likelihood of excellent/very good health with Medicare for both the uninsured and insured groups. The divergence is greater for the uninsured group. The other panels show the trajectories for the other health status categories. It is notable that by age 71 the fair/poor trajectories for the insured and uninsured groups converge.

As a check on the fit of our model and our simulation to the raw data on health status for our sample, we graphically display the raw trajectories with the trajectories from our fitted data in Figure 5. This dramatically demonstrates the remarkable fit of our model.

Table 5 displays the simulated incremental effects between health trajectories. In column [E] we see that for every 100 persons in the uninsured group, from age 65 to 71 the introduction of Medicare at age 65 leads to 7.7 more uninsured people reporting excellent or very good health, 6.1 fewer reporting good health, 3.7 fewer reporting fair or poor health, and 2.2 more are dead. The changes are statistically significant for the excellent/very good group, suggested by the exclusion of 0 in the reported 95% confidence interval. Similar but weaker patterns are observed for the insured group from age 65 to 71, where the introduction of Medicare at 65 leads to 5.9 more insured people reporting excellent or very good health, 5.1 fewer reporting good health, 1.0 fewer reporting fair or poor health, and 0.2 more are dead (column [F]). Medicare at age 65 appears to delay the erosion of excellent or very good health. For the uninsured group, the deterioration of health prevented is one that would have resulted in good, fair, or poor health. For the insured group, the deterioration of health prevented is one that would have resulted in good health. We could not detect a significant survival effect of Medicare at age 65.

The comparisons between the insured and uninsured groups in column [G] show 1.8 more reporting excellent or very good health in the uninsured group and 2.8 fewer reporting fair or poor in the uninsured group. Although not statistically significant, this does suggest that providing health insurance to the uninsured does has a modest health effect.

Table 6 displays results for various subgroups. There is a similar pattern when the analysis is limited to the continuously insured and the continuously uninsured. The uninsured enrolling into Medicare appears to have a slightly greatest positive influence on women compared with men in terms of the gain in excellent/very good health. The comparisons in the low-income and low-wealth groups look remarkably similar to the overall result. Finally, we compare the subgroup of those with supplemental versus those without supplemental insurance. The rates of death increase for both subgroups because those who died before 65 were dropped from both subgroups because supplemental status could not be determined. The relative difference between the uninsured and insured is greater for the uninsured who also obtain supplemental insurance.

Table 7 presents the sensitivity of the results to various alternatives. The results are insensitive to changes in retirement status, changes in marital status, or the introduction of Social Security payments suggesting that the difference within the insured and uninsured groups cannot be attributed to these often contemporaneous changes at age 65. The results are insensitive to alternative age specifications. Our main concern is that our use of a quadratic age specification was not appropriately capturing the non-linear trajectory of health status with age. In this series of robustness checks, we find almost no non-linear pattern of health status changes and age. The three alternative age specifications considered (i.e., 2a, 2b, and 2c in Table 7) are nearly identical to the base model, suggesting that we have appropriately specified the age/health trajectory. Panel 3 in Table 7 shows the model when the five living health states are not collapsed into three living health states. The three health states used in the base model potentially mask some differences between the excellent and very good health states, and between the fair and poor health states, but the smaller sample sizes in the finer categories leads to less precise estimates. Generally, the combined groups are a fair representation of the more specific patterns in this panel. When the five categories of health status in the multinomial logit but summarizes the results in the same way as the base model. Here the results are similar to the base model.

Panel 4 in Table 7 shows the results excluding the weights. The weighting slightly increases the additional number of persons with excellent/very good health and this increase is greater in the uninsured group. Given the greater rates of attrition among the uninsured, the weighted estimate offers an appropriate adjustment for the observable attrition differences between groups.

VII. Conclusion

Because the number of near elderly is rising rapidly and there are few affordable alternatives for health insurance for those who lack access to employment-based coverage, the uninsured near-elderly are of growing concern. We find that providing Medicare to the near-elderly uninsured increases their probability of being in excellent or very good health, decreases their probability of being in good health, and has no statistically significant effects at lower health levels. Surprisingly, we found Medicare had the same pattern of effect on the health of the previously insured. This suggests that Medicare helps the relatively healthy 65 year olds, but may do little for those who are already in declining health once they reach the age of 65. The improvement in health from Medicare for the uninsured was not statistically different from the improvement in health from Medicare for the insured. However, the direction of the statistically insignificant effect is suggestive of a greater health effect for the previously uninsured.

Our evidence of Medicare improving the health status for the uninsured is consistent with evidence that the lack of health insurance in the period immediately preceding Medicare eligibility is associated with faster declines in health (Baker et al., 2001; Dor, Sudano, and Baker, 2006) and suggests that Medicare may attenuate the rapid health declines of the uninsured. It is also consistent with the conclusions of Hadley and Waidmann (2006) who, using an instrumental variables analysis approach with pre-65 HRS data only, summarize their findings as suggesting that extending insurance coverage to the near-elderly uninsured would result in an increase in the proportion of people at age 65 in excellent and very good health. Yet, as pointed out in a commentary by Kronick (2006), the magnitude of the health changes found in Hadley and Waidmann (much larger than those found here) seem implausible. Part of this may be due to issues with the appropriateness of their instruments, but part may be due to their use of an inappropriate instrumental variables estimator for nonlinear estimators for endogenous categorical health status and dependent variables (Newey, 1987; Terza, 2006). Another possible explanation for the differences between their results and ours is their use of an ordered logit. As our Technical Appendix indicates, these data reject that specification of the model. Moreover, Finkelstein and McKnight (2005) found, using aggregate data, that the establishment of Medicare had no discernible impact on the mortality of the elderly in the decade after the enactment of Medicare.

The potential for health improvements for the uninsured is supported by the evidence that use of medical services rises dramatically after enrollment into Medicare and that the increase is greater for those who become insured when they are eligible for Medicare than for those who were insured before Medicare enrollment. This effect of Medicare on health service use may be the mechanism for the positive effects on health status. Yet this mechanism is not entirely consistent with our finding that health status also improved for those who enrolled into Medicare at age 65 and were insured before this age. To be consistent with an improvement in health for both the previously insured and previously uninsured, the mechanism would have to include aspects of the Medicare program that are different from insurance obtained in the private market. For example, Medicare offers a more stable source of health insurance which may itself have a health advantage because the decision to leave work when one is recovering from an illness may improve recovery (Bradley et al., 2005). This might outweigh the possibility that insurance coverage under Medicare may be less generous, on average, when compared to employer-sponsored health insurance, even in the presence of private supplemental coverage that is obtained by many Medicare beneficiaries. If, in fact, the stability of insurance coverage afforded by Medicare is the source of the health benefit, universal coverage at other ages may have similar health effects.

An alternative explanation for health improvements at 65 would be if health changes resulted from contemporaneous changes at age 65, such as retirement and Social Security payments. Because the majority initiate retirement and social security prior to 65, rather than contemporaneous with Medicare eligibility, we were able to separately identify these events and add controls for initiation of retirement and Social Security. This alternative explanation was not supported by our data because when we added these controls, the changes to health observed at Medicare eligibility remained. Another alternative may be that the observed changes in health status could be attributed to subjective responses to the health status question. This study is limited by its use of self-reported health status rather than objectively determined health status measures. Further research into the mechanisms generating the effects measured in this paper is still needed.

We find that Medicare does improve the health of the uninsured and the insured, but only for the relatively healthy. This suggests that there are health benefits of universal coverage and that extending this coverage to much earlier ages may increase the proportion of the population who arrive at the age of 65 in excellent or very good health. It also suggests that Medicare itself may be providing health benefits to the population. When considering the value of health insurance, however, health is only one important aspect. Health insurance is designed to provide financial security to families by protecting them from potentially devastating financial consequences that can result from unexpected health care expenses (Himmelstein, et al., 2005). The more direct financial justification for health insurance should not be forgotten as we seek to better understand its indirect health consequences.

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Figure 1. Model of health effect at 65

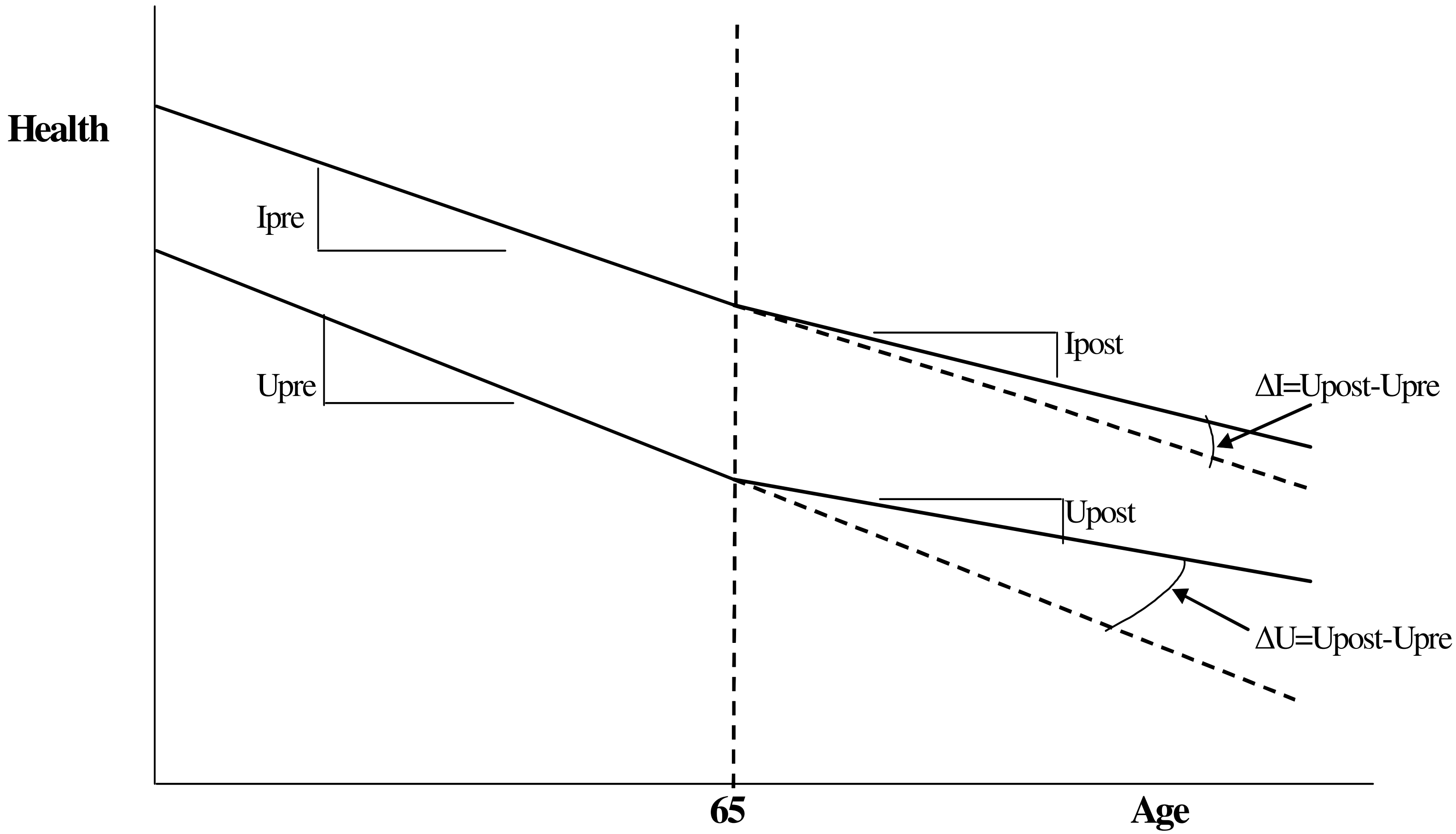


Figure 2. Ages in Pre and Post Group Samples

birth year	SURVEY YEAR 1992	1994	1996	1998	2000	2002	2004
	(AGE IN SURVEY YEAR IS LISTED BELOW)						
1941	51	53	55	57	59	61	63
1940	52	54	56	58	60	62	64
1939	53	55	57	59	61	63	65
1938	54	56	58	60	62	64	66
1937	55	57	**59**	61	63	**65**	67
1936	56	58	**60**	62	64	**66**	68
1935	57	**59**	61	63	**65**	67	69
1934	58	**60**	62	64	**66**	68	70
1933	**59**	61	63	**65**	67	69	71
1932	**60**	62	64	**66**	68	70	72
1931	61	63	**65**	67	69	71	73

Figure 3. Health effects from the empirical model

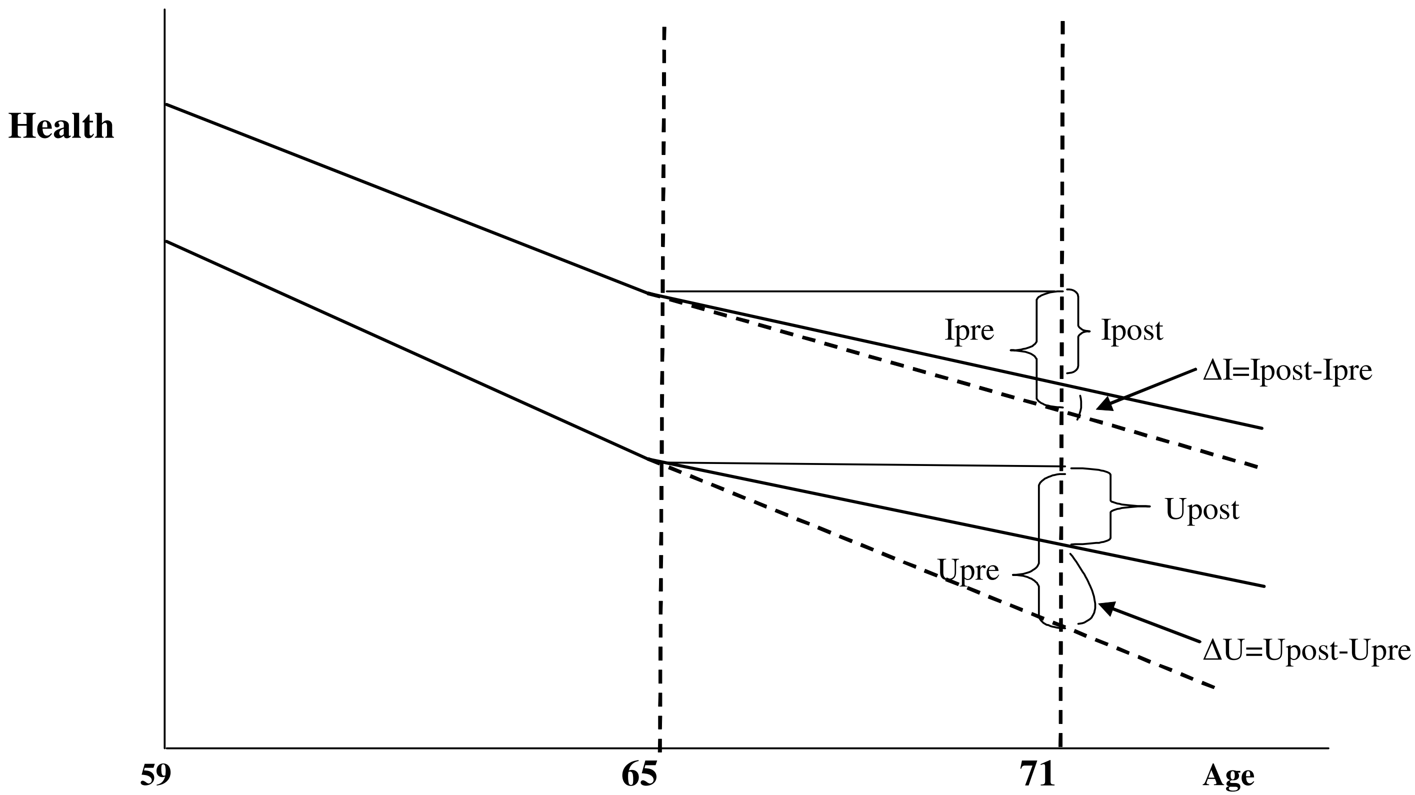
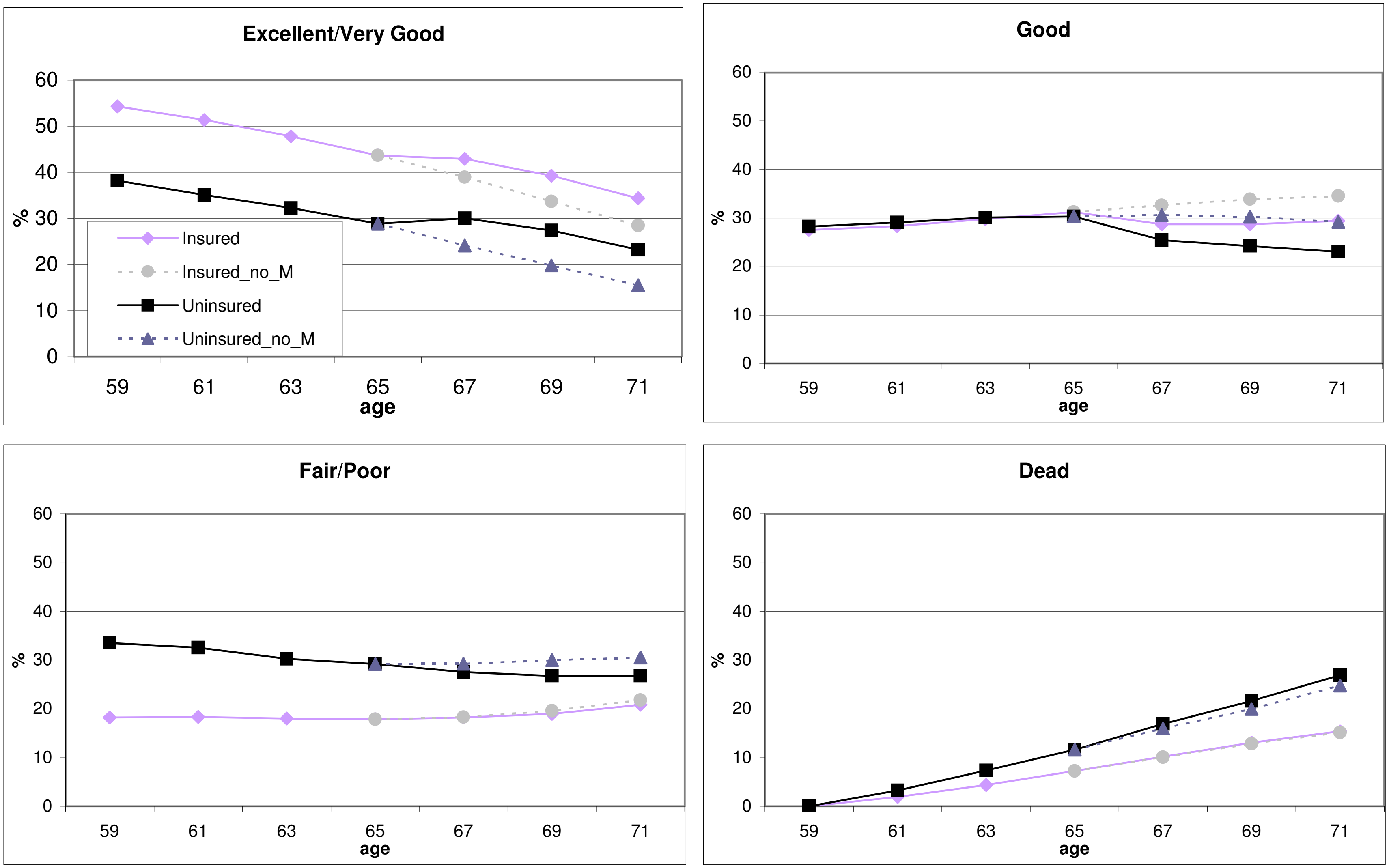
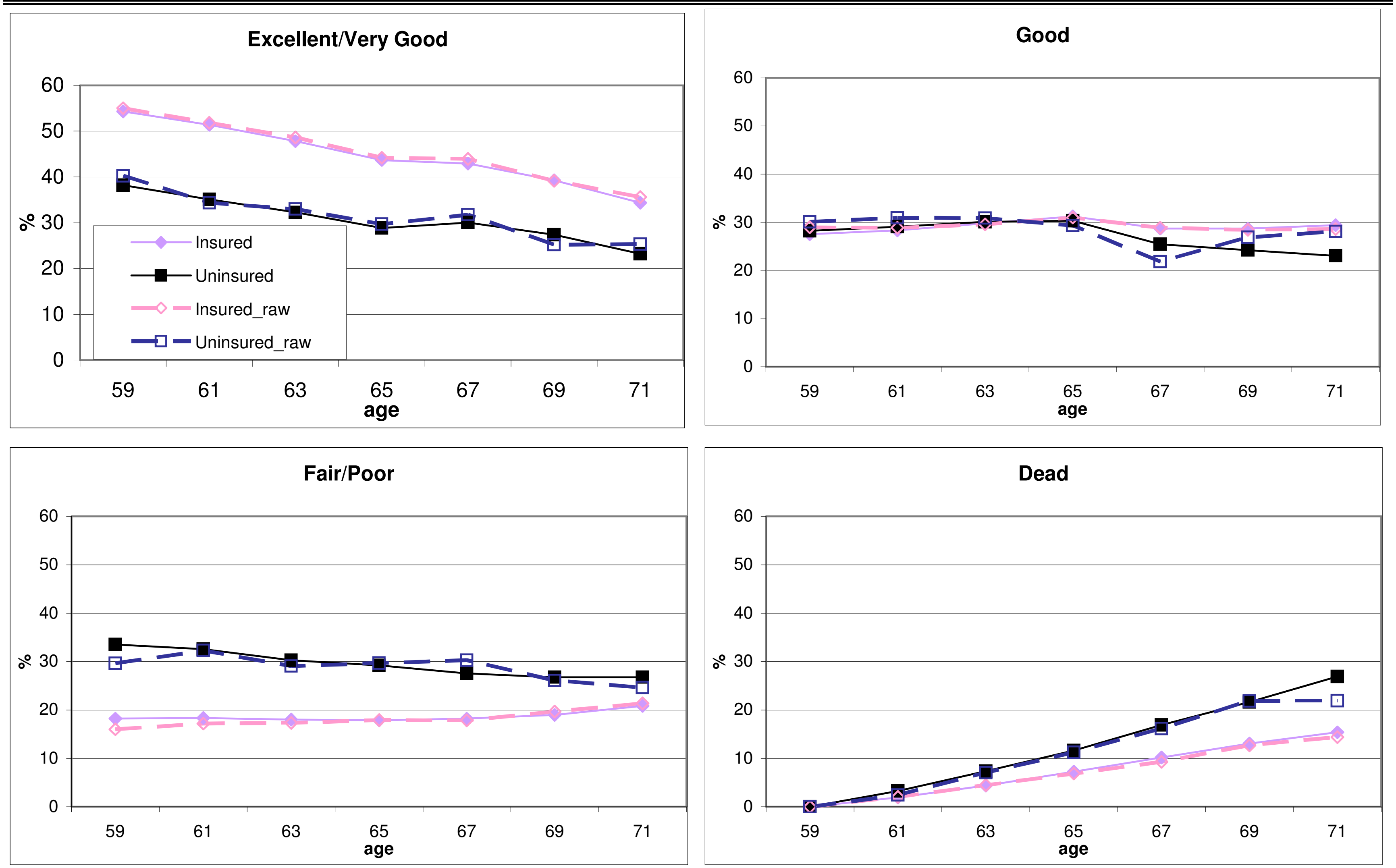


Figure 4. Health Status Trajectories by Insurance Group from Simulation*



***Adjusted for sex, age, education, ethnicity, race and region**

Figure 5. Health Status Trajectories by Insurance Group from Simulation* and from Raw Data



***Adjusted for sex, age, education, ethnicity, race and region**

Table 1. Selection of Study Sample

Selection Criteria	N	Group excluded	N Excluded
Total age eligible, cohorts 1931-1941	9,771		
Survey wave for cohort at age 59/60	9,234	Age cohort 1931	537
Two survey waves for cohort before age 65	5,086	Age cohorts 1938-1941	4,148
Interviewed at age age 59/60	4,994	Deceased before age 59/60	92
	4,860	Unobserved at age 59/60	134
Insurance status observed in 1992	4,805	No initial insurance status	55
Covered by Medicare after 65	4,774	Post-65 uninsured	31
More than one follow-up	4,647	No follow-ups	127
Not on Medicare or Medicaid at 59/60	4,075	Medicare or Medicaid at 59/60	572

Table 2. Insurance Groups

Insurance Groups	Total N	Total Weighted %	Pre-Period N	Pre-Period Weighted %	Post-Period N	Post-Period Weighted %
	Subjects					
	Insurance status at age 59/60					
Insured	3484	85.5	3484	85.5	3256	86.0
Uninsured	591	14.5	591	14.5	524	14.0
Total	4075	100.0	4075	100.0	3780	100.0
	Observations					
	Insurance status at age 59/60					
Insured	16511	85.7	10236	85.6	6275	86.0
Uninsured	2727	14.3	1712	14.4	1015	14.0
Total	19238	100.0	11948	100.0	7290	100.0

Table 3. Baseline characteristics of insured and uninsured

	Insured N=3484	Uninsured N=591	P-value of difference*
Health Status			
Excellent/Very good	54.9%	40.4%	<0.001
Good	29.0%	30.0%	0.615
Fair/Poor	16.1%	29.6%	<0.001
Male	48.2%	46.3%	0.394
Race			
White	86.2%	65.4%	<0.001
Black	7.7%	14.6%	<0.001
Hispanic	4.2%	15.8%	<0.001
Other	1.8%	4.2%	<0.001
Education			
High school drop-out	17.6%	45.7%	<0.001
High school graduate	41.6%	32.9%	<.0001
Some college	20.0%	13.1%	<0.001
College graduate	20.8%	8.3%	<0.001
Marital status			
Married	79.3%	68.6%	<0.001
Single	3.1%	3.5%	0.665
Divorced/Separated	10.5%	16.3%	<.0001
Widowed	7.1%	11.6%	<0.001
Region			
Midwest	26.8%	14.7%	<0.001
Northeast	21.6%	16.7%	0.007
South	32.2%	45.9%	<0.001
West	19.4%	22.7%	0.065
Total Assets			
Negative	1.9%	7.9%	<0.001
0-35,000	9.7%	32.6%	<0.001
35,001-100,000	15.7%	16.8%	0.496
100,001-230,000	26.0%	17.0%	<0.001
230,001 and above	46.7%	25.8%	<0.001
Total Income			
0-20,000	12.4%	48.0%	<0.001
20,001-40,000	22.5%	25.1%	0.161
40,001-75,000	34.2%	15.1%	<0.001
75,001 and above	31.0%	11.8%	<0.001
Social Security Recipient	4.5%	7.6%	0.001
Retirement Status			
Not Retired	61.8%	57.6%	0.051
Fully Retired	20.1%	14.6%	0.002
Partly Retired	9.8%	10.1%	0.792
Not Applicable	8.3%	17.7%	<.0001

*P-values for all group tests are significant at .05 level

Table 4. Multinomial Logit Regression of Health Status in t+1

	Good vs. Exc/VG		Fair/Poor vs. Exc/VG		Dead vs. Exc/VG	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Health Status						
Good	1.89	<.001	2.28	<.001	1.49	<.001
Fair/Poor	2.38	<.001	4.75	<.001	4.07	<.001
Uninsured	0.27	0.030	0.47	0.018	0.49	0.180
Post (Medicare)	-0.26	0.008	-0.16	0.304	-0.54	0.090
Uninsured*Health Status						
Good	-0.26	0.208	-0.21	0.403	-0.01	0.992
Fair/Poor	-0.50	0.073	-0.67	0.045	-0.51	0.293
Post (Medicare)*Health Status						
Good	-0.06	0.521	-0.08	0.633	0.53	0.130
Fair/Poor	0.14	0.474	0.17	0.433	0.65	0.066
Uninsured*Post (Medicare)	-0.46	0.028	0.15	0.632	0.92	0.114
Uninsured*Post (Medicare)*Health Status						
Good	0.36	0.295	-0.36	0.365	-1.30	0.098
Fair/Poor	0.17	0.715	-0.64	0.183	-1.23	0.099
Age	0.07	<.001	0.08	<.001	0.07	0.053
Age*Age	0.00	0.561	0.01	0.030	-0.01	0.051
Male	0.08	0.069	0.17	0.002	0.70	<.001
Race/Ethnicity						
Black	0.28	<.001	0.41	<.001	0.40	0.004
Hispanic	0.35	0.001	0.39	0.001	-0.30	0.182
Other Race	0.45	0.013	0.22	0.237	-0.15	0.687
Education						
High School Graduate	-0.27	<.001	-0.66	<.001	-0.44	0.001
Some College	-0.30	<.001	-0.85	<.001	-0.63	<.001
College Graduate	-0.52	<.001	-1.25	<.001	-0.86	<.001
Region						
Northeast	-0.08	0.267	-0.08	0.370	0.04	0.816
South	-0.03	0.593	0.18	0.009	0.16	0.236
West	-0.24	0.001	0.07	0.442	0.01	0.971

P-value of the X^2 Tests on the set of coefficients representing the following Null Hypotheses:

Hypothesis:	P-value
Upre = Ipre	0.095
Upost = Ipost	0.001
Upre = Upost	0.034
Ipre = Ipost	0.066
(Upost - Upre) = (Ipost - Ipre)	0.110

Table 5. Predicted Probabilities of Health Status Changes Simulated between Age 65 and 71

	U post	U pre	I post	I pre	ΔU	ΔI	ΔU - ΔI
					[A] - [B]	[C] - [D]	[E] - [F]
	[A]	[B]	[C]	[D]	[E]	[F]	[G]
N=	1015 (5.3%)	1712 (8.9%)	6275 (32.6%)	10236 (53.2%)			
Excellent/VG	-5.7	-13.4	-9.3	-15.2	7.7	5.9	1.8
					(2.5, 12.3)	(0.8, 8.9)	(-2.6, 7.0)
Good	-7.2	-1.1	-1.8	3.3	-6.1	-5.1	-1.0
					(-13.5, -1.4)	(-9.3, -1.5)	(-7.2, 3.2)
Fair/Poor	-2.4	1.3	3.0	4.0	-3.7	-1.0	-2.8
					(-8.1, 3.6)	(-4.1, 3.4)	(-6.8, 3.2)
Dead	15.3	13.2	8.1	7.9	2.2	0.2	1.9
					(-3.9, 7.5)	(-2.7, 2.5)	(-3.2, 6.5)

Adjusted for sex, age, education, ethnicity, race and region

Table 6. Subgroup Analysis

	U post	U pre	I post	I pre	ΔU	ΔI	ΔU - ΔI
					[A] - [B]	[C] - [D]	[E] - [F]
	[A]	[B]	[C]	[D]	[E]	[F]	[G]
1. Continous Insurance Status Subgroups							
a. Continuously Uninsured (U) vs. Continuously Insured (I)							
N=	509 (3.0%)	886 (5.2%)	5925 (34.9%)	9665 (56.9%)			
Excellent/VG	-4.6	-12.2	-10.0	-16.0	7.6	6.0	1.6
					(1.4, 12.8)	(0.6, 9.5)	(-3.7, 8.3)
Good	-11.2	-4.4	-2.0	2.5	-6.8	-4.6	-2.3
					(-14.2, -0.5)	(-8.4, 0.0)	(-9.5, 3.1)
Fair/Poor	1.8	2.6	3.8	5.7	-0.7	-1.9	1.2
					(-8.1, 8.7)	(-6.0, 2.3)	(-5.3, 9.4)
Dead	13.9	13.9	8.2	7.8	-0.1	0.4	-0.5
					(-6.7, 5.9)	(-2.1, 3.1)	(-7.1, 5.0)
b. Continuously Uninsured (U) vs. Continuously Privately Insured (I)							
N=	509 (3.2%)	886 (5.6%)	5500 (34.7%)	8976 (56.6%)			
Excellent/VG	-4.5	-11.7	-10.1	-16.4	7.3	6.3	0.9
					(2.4, 14.0)	(2.0, 11.1)	(-5.0, 7.4)
Good	-10.7	-4.1	-1.8	3.4	-6.6	-5.1	-1.4
					(-14.3, 0.4)	(-9.3, -0.4)	(-9.1, 5.0)
Fair/Poor	1.8	4.3	4.3	6.3	-2.5	-2.0	-0.5
					(-11.0, 5.3)	(-6.4, 1.9)	(-8.3, 6.7)
Dead	13.4	11.5	7.6	6.8	1.9	0.8	1.0
					(-4.3, 9.0)	(-2.2, 2.9)	(-4.3, 8.7)
2. Sex Subgroups							
a. Female							
N=	562 (5.6%)	937 (9.3%)	3285 (32.6%)	5298 (52.6%)			
Excellent/VG	-3.5	-11.7	-9.5	-15.3	8.2	5.9	2.3
					(-2.6, 13.1)	(-4.5, 7.4)	(-3.3, 11.4)
Good	-6.3	0.6	-1.9	3.2	-6.8	-5.1	-1.7
					(-14.9, 0.7)	(-9.3, 1.9)	(-10.2, 3.6)
Fair/Poor	-3.3	0.3	2.8	3.6	-3.6	-0.9	-2.7
					(-10.0, 6.7)	(-3.4, 6.1)	(-9.9, 4.5)
Dead	13.1	10.8	8.6	8.5	2.3	0.1	2.2
					(-4.2, 8.6)	(-3.6, 3.1)	(-3.9, 8.3)
b. Male							
N=	453 (5.0%)	775 (8.5%)	2990 (32.7%)	4938 (53.9%)			
Excellent/VG	-6.7	-14.2	-9.4	-15.5	7.5	6.1	1.4
					(3.5, 16.8)	(3.5, 13.5)	(-5.9, 8.4)
Good	-8.2	-2.6	-1.8	3.4	-5.6	-5.2	-0.4
					(-16.1, 0.2)	(-11.9, -0.7)	(-9.0, 6.1)
Fair/Poor	-0.4	4.0	3.2	4.1	-4.4	-1.0	-3.4
					(-12.2, 5.5)	(-7.9, 3.1)	(-8.7, 6.5)
Dead	15.3	12.8	8.1	7.9	2.5	0.1	2.4
					(-7.8, 9.5)	(-4.1, 3.3)	(-6.5, 9.0)

Table 6 (continued). Subgroup analysis

3. Low Income and Wealth Subgroups							
a. Below Median Income							
N=	826 (8.8%)	1393 (14.8%)	2684 (28.5%)	4511(47.9%)			
Excellent/VG	-5.1	-12.4	-7.7	-13.4	7.3	5.7	1.6
					(-2.6, 9.8)	(-3.7, 6.9)	(-3.2, 7.9)
Good	-7.0	-1.3	-2.4	2.7	-5.7	-5.2	-0.6
					(-14.0, -0.4)	(-10.0, 0.4)	(-9.1, 3.8)
Fair/Poor	-3.1	0.7	1.9	2.8	-3.7	-1.0	-2.8
					(-10.4, 4.5)	(-2.9, 7.1)	(-11.0, 1.4)
Dead	15.2	13.0	8.3	7.9	2.2	0.4	1.7
					(-1.4, 11.7)	(-3.4, 3.6)	(-0.8, 10.9)
b. Below Median Wealth							
N=	727 (7.6%)	1263 (13.3%)	2816 (29.6%)	4702 (49.5%)			
Excellent/VG	-5.7	-11.9	-8.6	-13.9	6.2	5.3	0.9
					(2.3, 11.7)	(1.7, 10.1)	(-4.1, 6.3)
Good	-7.0	-2.3	-2.8	2.0	-4.7	-4.8	0.1
					(-8.8, 4.3)	(-9.2, 1.8)	(-5.0, 7.7)
Fair/Poor	-3.6	0.1	2.2	3.1	-3.7	-0.9	-2.8
					(-9.0, 6.0)	(-5.2, 5.9)	(-8.9, 4.6)
Dead	16.3	14.1	9.2	8.7	2.2	0.4	1.7
					(-12.2, 4.4)	(-9.3, 1.3)	(-7.5, 7.2)
4. Medicare Supplemental Insurance Status Subgroups							
a. Medicare with No Supplemental Insurance							
N=	579 (7.2%)	921 (11.4%)	2551 (31.6%)	4032 (49.9%)			
Excellent/VG	-9.0	-14.5	-11.6	-14.1	5.5	2.4	3.1
					(-2.1, 13.3)	(-4.3, 8.6)	(-4.1, 10.7)
Good	-10.2	2.2	-2.4	6.3	-12.4	-8.7	-3.6
					(-21.2, -3.1)	(-15.8, -2.0)	(-11.1, 4.0)
Fair/Poor	3.0	12.3	4.3	7.7	-9.3	-3.5	-5.9
					(-19.9, 1.8)	(-10.9, 2.7)	(-13.7, 3.0)
Dead	16.2	0.0	9.8	0.0	16.2	9.8	6.4
					.	(8.2, 21.2)	.
b. Medicare with Supplemental Insurance							
N=	436 (4.1%)	651 (6.2%)	3724 (35.3%)	5736 (54.4%)			
Excellent/VG	-2.5	-8.8	-8.9	-15.1	6.3	6.2	0.1
					(-3.2, 15.9)	(-0.3, 12.8)	(-8.3, 8.4)
Good	-6.0	2.0	-1.8	7.0	-8.1	-8.8	0.8
					(-20.0, 1.6)	(-15.5, -2.9)	(-9.2, 9.3)
Fair/Poor	-6.8	6.8	2.7	8.1	-13.6	-5.4	-8.2
					(-24.6, -2.6)	(-12.5, 1.3)	(-16.9, 1.4)
Dead	15.4	0.0	8.0	0.0	15.4	8.0	7.4
					.	(6.4, 17.2)	.
c. Medicare with Supplemental Insurance and pre-65 continuous private health insurance							
N=	509 (5.2%)	819 (8.4%)	3277 (33.7%)	5106 (52.6%)			
Excellent/VG	-4.0	-10.4	-8.6	-13.4	6.3	4.8	1.6
					(-0.7, 13.8)	(-1.6, 10.8)	(-5.4, 9.7)
Good	-13.9	-6.0	-4.1	1.5	-7.9	-5.6	-2.3
					(-17.7, -0.9)	(-11.8, 0.5)	(-10.7, 5.2)
Fair/Poor	2.9	16.4	5.1	11.8	-13.5	-6.7	-6.8
					(-23.3, -1.9)	(-13.7, -0.5)	(-14.9, 4.0)
Dead	15.1	0.0	7.6	0.0	15.1	7.6	7.5
					.	(7.8, 18.3)	.

Table 7. Sensitivity Analysis

	U post	U pre	I post	I pre	ΔU [A] - [B]	ΔI [C] - [D]	ΔU - ΔI [E] - [F]
	[A]	[B]	[C]	[D]	[E]	[F]	[G]
1. Adding Potential Endogenous Covariates							
a. Time-varying Retirement Status							
Excellent/VG	-5.4	-13.1	-9.2	-15.1	7.7	5.9	1.8
Good	-7.5	-1.3	-1.8	3.3	-6.2	-5.1	-1.1
Fair/Poor	-2.1	1.7	3.0	4.0	-3.7	-1.0	-2.7
Dead	14.9	12.8	8.0	7.9	2.2	0.2	2.0
b. Time-varying Social Security Recipient Status							
Excellent/VG	-5.6	-13.3	-9.3	-15.2	7.7	5.9	1.8
Good	-7.3	-1.2	-1.7	3.4	-6.1	-5.1	-1.0
Fair/Poor	-2.5	1.2	2.9	3.9	-3.7	-1.0	-2.7
Dead	15.4	13.3	8.1	7.9	2.1	0.3	1.8
c. Time-varying Retirement Status, Social Security Recipient Status, and Marital Status							
Excellent/VG	-5.4	-12.9	-9.2	-15.0	7.6	5.8	1.7
Good	-7.0	-1.3	-1.6	3.3	-5.8	-5.0	-0.8
Fair/Poor	-2.5	1.5	2.9	3.9	-4.0	-1.0	-3.0
Dead	15.0	12.7	7.9	7.8	2.3	0.1	2.1
d. Baseline Marital Status, Income, and Wealth							
Excellent/VG	-4.7	-12.6	-9.4	-15.3	7.8	6.0	1.8
Good	-7.1	-0.9	-1.7	3.5	-6.2	-5.2	-1.0
Fair/Poor	-2.8	0.9	2.9	3.8	-3.6	-1.0	-2.7
Dead	14.6	12.6	8.2	8.0	2.1	0.2	1.9
2. Alternative Age Specifications							
a. Linear Age							
Excellent/VG	-5.2	-12.4	-8.7	-14.3	7.3	5.6	1.7
Good	-6.9	-0.6	-1.5	3.7	-6.2	-5.3	-1.0
Fair/Poor	-4.3	-1.3	1.5	1.8	-3.0	-0.3	-2.7
Dead	16.3	14.3	8.7	8.8	2.0	-0.1	2.0
b. Interaction of Age and Health Status							
Excellent/VG	-4.9	-12.5	-8.7	-14.5	7.6	5.8	1.8
Good	-7.1	-1.4	-1.5	3.6	-5.7	-5.1	-0.5
Fair/Poor	-4.2	-0.5	1.5	2.1	-3.8	-0.5	-3.2
Dead	16.2	14.3	8.7	8.8	1.9	-0.1	2.0
c. Interaction of Age and Health Status, and Age-Squared and Health Status							
Excellent/VG	-5.8	-13.4	-9.3	-15.3	7.6	6.0	1.7
Good	-7.3	-1.1	-1.8	3.3	-6.2	-5.1	-1.1
Fair/Poor	-2.2	1.3	3.0	4.1	-3.6	-1.1	-2.5
Dead	15.4	13.2	8.1	7.9	2.2	0.2	1.9

Table 7 (continued). Sensitivity Analysis

3. Alternative of Health Status Categorization							
a. Health Status: 5 Categories							
Excellent	-1.5	-4.3	-5.1	-4.7	2.8	-0.3	3.1
Very Good	-3.9	-8.1	-4.5	-9.5	4.2	5.1	-0.8
Good	-7.5	-2.4	-1.9	2.7	-5.2	-4.6	-0.6
Fair	-1.7	-1.1	1.6	1.9	-0.6	-0.3	-0.3
Poor	-0.6	3.0	1.7	2.1	-3.6	-0.4	-3.3
Dead	15.2	12.9	8.1	7.6	2.3	0.5	1.8
b. Health Status 5 Categories Summarized as 3 Categories (E/VG, G, F/P)							
Excellent/VG	-5.4	-12.4	-9.5	-14.3	7.0	4.8	2.3
Good	-7.5	-2.4	-1.9	2.7	-5.2	-4.6	-0.6
Fair/Poor	-2.3	1.9	3.3	4.0	-4.2	-0.6	-3.5
Dead	15.2	12.9	8.1	7.6	2.3	0.5	1.8
4. Sensitivity to Survey Weight							
Excellent/VG	-4.4	-10.4	-9.0	-14.1	6.1	5.0	1.0
Good	-10.7	-4.5	-2.9	1.0	-6.3	-3.8	-2.4
Fair/Poor	-1.3	1.2	3.0	4.5	-2.5	-1.5	-1.0
Dead	16.4	13.7	8.9	8.6	2.7	0.4	2.4
5. Including People with Medicare/Medicaid at Age 59/60							
Excellent/VG	-4.4	-12.7	-8.0	-14.5	8.3	6.5	1.8
Good	-7.8	-0.7	-1.9	2.9	-7.0	-4.8	-2.2
Fair/Poor	-3.1	0.8	1.6	2.9	-3.9	-1.3	-2.6
Dead	15.3	12.7	8.3	8.7	2.6	-0.5	3.1

TECHNICAL APPENDIX

In this technical appendix, we provide additional details about the data, the sample used, the specification of the model, and assorted sensitivity tests to verify the robustness of our results.

Differential sample loss. One of our early analyses indicated that there was differential sample loss for the initially uninsured from the initial cohort of the HRS. For example, while the overall rate of loss to follow-up is 7.4% in the 1994 HRS (Baker and Sudano, 2005), we estimated this rate to be 6.7% among the insured and 13.8% among the uninsured. (Polsky et al., 2005). This dropout pattern continues in all survey waves and is not accounted for in HRS survey weights. The respondent levels weights in the HRS are scaled so as to yield weight sums which correspond to the number of individuals in the U.S. population as measured by the March CPS for the year of data collection. Existing HRS methodology involves post-stratifying each wave's weights to the corresponding March CPS on the basis of age of respondent and spouse and on the basis of respondent gender and race/ethnicity. Since insurance status was not factored into the weight estimation strategy by the HRS, we made additional adjustments to the respondent-level weights in the HRS so as to account for this differential dropout by insurance status in the HRS.

To create additional weight adjustment factors for the HRS using the Current Population Survey's (CPS) March supplement as a benchmark so that the weights would account for population level incidence of being uninsured we followed for following steps. First, we created mutually exclusive categories within 4 dimensions related to insurance status: insurance categories defined as mutually exclusive insurance groups using hierarchical assignment (Employer/ Individual, Medicaid / Medicare / VA/Champus, Uninsured), race/ethnicity categories (White/Other (non-Hispanic), Black (non-Hispanic), All Hispanic), education categories (<high school degree, >=high school degree), and labor force participation categories (in labor force, not in labor force). Second, for respondents at age 59/60 in the 1992, 1994, and 1996 March CPS we estimated weighted and unweighted frequency counts for the 36 cells defined by: insurance groups * race* education * labor force status. Cells smaller than n=20 were collapsed. Third, we similarly estimated weighted and unweighted counts for our study sample of 59/60 year olds in the 1992, 1994, and 1996 HRS for the 36 cells defined by insurance groups * race* education * labor force status. Fourth, an adjustment factor was calculated as the ratio of the weighted CPS count to the weighted HRS count within each of the 36 cells. Fifth, these insurance-race-education-labor force status- specific adjustment factors were applied to each individual's HRS wave-specific weight in our study sample of 59/60 year olds in 1992, 1994, or 1996. Hence, by applying the adjustments, our study estimates from the HRS were benchmarked with the CPS.

Design Effects. For all of our subsequent analysis, we have adjusted for the design effects in the original study and for the differential sample loss by using these revised weights.

We also correct for the panel nature of our data – repeated observations on individuals over a twelve year period. In the estimation stage, and tests on the estimated equations, we use robust (Huber-White-Eicker) corrections appropriate to the estimator, and include cluster corrections at the person ID level using SAS SURVEYLOGIT procedure with the cluster option. In predicting the trajectories from these estimates, we use estimates based on a clustered nonparametric bootstrapping of the data, where the clusters are all of the observations on an individual. Each of the thousand replicates' parameter estimates are used to make predictions based on a fixed reference sample. That sample includes 100 copies of the values for our sample at age 59/60, with the weights equal to the weights at that age. The reason for the additional copies was to reduce the extra variation induced by our Monte Carlo simulation of the trajectories for categorical health outcomes (see below).

No formal correction is made for the clustering of observations by PSU's in the Health and Retirement Study.

<u>Estimation approach to health transitions</u>. Because **s**elf-reported health status (augmented with being dead as the worst alternative) is an ordered categorical variable, one of the logical choices for analyzing the response in ordered data is either the ordered logit or the ordered probit. In contrast, our multinomial approach does not exploit the information contained in the ordering. In our sensitivity analyses, we examined the ordered logit and an extension, the generalized ordered logit (Williams, 2006). The ordered logit estimator is highly restrictive in that it assumes proportional odds (or parallel lines). The multinomial logit removes the ordering assumption between categories at the expense of increasing the number of parameters estimated. The generalized ordered logit model is a partial proportional odds model that preserves the information from ordering, but loosens the restrictive proportional odds assumption when it is violated. In our case, the generalized ordered logit estimated the same number of parameters as the multinomial logit. We use a Richard William's *gologit2* command in STATA for the partial proportional response model. Although the formulation is slightly different, the model is equivalent to Lall et al. (2002) and Peterson and Harrell (1990).

To test the proportional property of the ordered logit, we performed the Brant Test (Brant, 1990) The resulting test value in Appendix Table 1 indicates that we can reject the ordered logit at $p < 0.001$; the proportionality assumption does not hold for these data. Moreover, an examination of the specific contributors to the overall test value suggests that several key explanatory variables are involved, including initial health good and fair/poor and the specification of age, which is confounded with Medicare status. The *eliunin* variable is a key violation given that it represents the interaction between Medicare eligibility and being uninsured at age 59/60.

We also used other specification tests to assess the alternative estimators. We employed the modified Hosmer–Lemeshow Test to determine whether there was a relationship between the raw-scale residuals (indicators for each status minus their predicted probability) against indicators for deciles of each of the predicted probabilities from these three models (ordered logit, generalized ordered logit, and multinomial). We show the F-statistics from test of whether deciles of the predicted probability to determine if there is any systematic misfit in the predictions over the range of the data. If the specification is appropriate, we would expect that the raw-scale residuals would not be significantly different from zero as we move from low predicted values to high predicted values. Appendix Table 2 and Appendix Figure 1 provide the results of these tests. These tests suggest that the ordered logit does not fit these data well. The ordered logit is unable to capture the movement to dead at the higher levels of predicted probabilities. [Given the Brant test result above, part of this is the failure of the data to satisfy the proportionality assumption.] The generalized ordered logit and the multinomial logit behave fairly well and yield similar predictions to each other. They do not appear to be systematically biased over sub ranges of the data. Given the similarity in predicted trajectories for the multinomial and the generalized ordered logit estimators, we decided to employ the multinomial model, because it is more widely known. At worst the price for this may be some loss of precision.

We also assessed each of the estimators using appropriate extensions of Pregibon's Link Test and the Ramsey's RESET Test. Our specification failed for all three estimators [Not shown].

We also test the fit for the multinomial logit and the ordered logit (this command was unavailable for the generalized ordered logit) using the Log Likelihood, AIC and Schwartz criteria. See Appendix Table 3.

Finally we provide the regression output for the ordered logit and the generalized ordered logit in Appendix Tables 4a and 4b. This output is analogous to the multinomial regression which is Table 4 in the paper.

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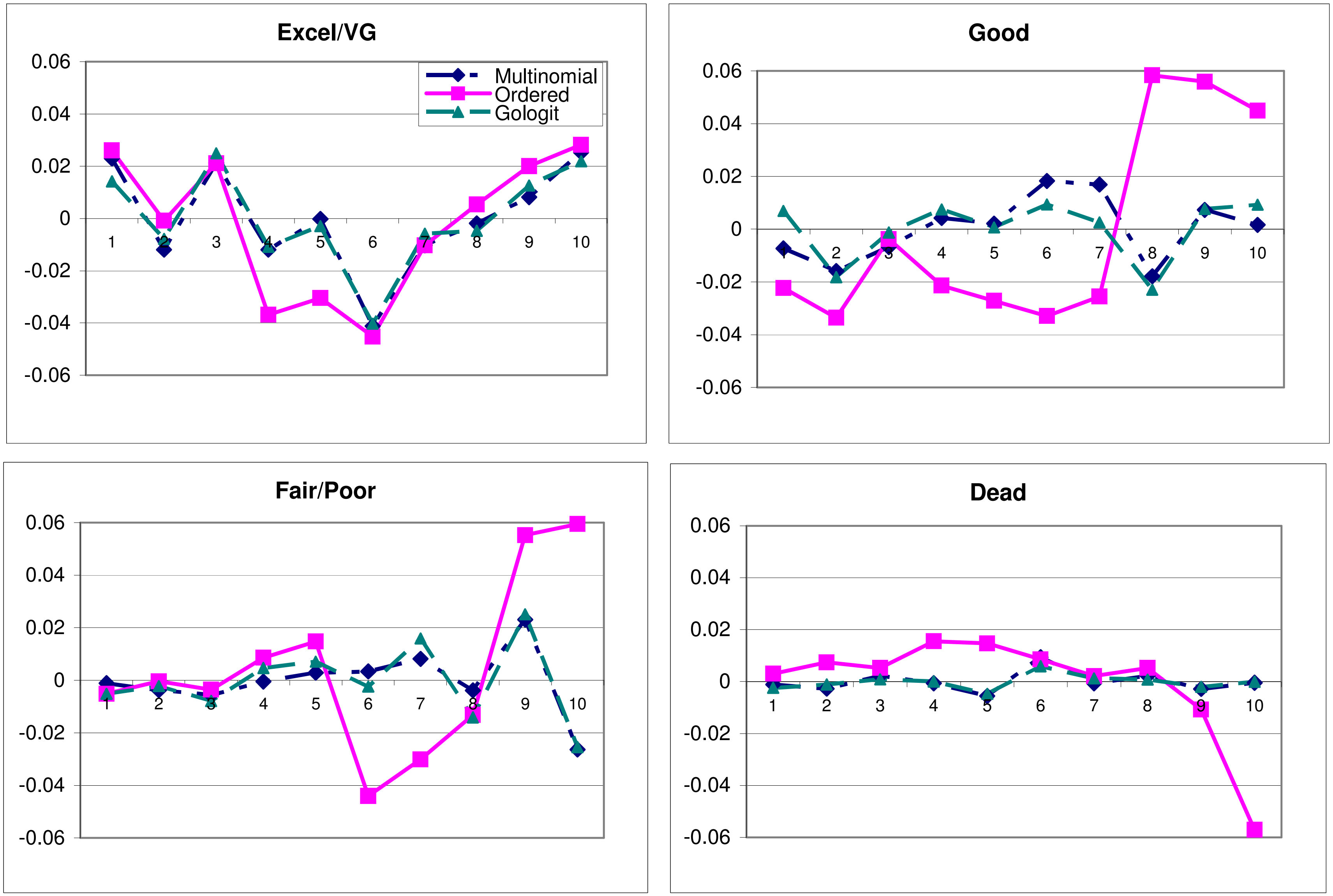
Appendix Figure 1: Revised Hosmer–Lemeshow Test

Mean of residuals for each decile of the predicted probability by regression model



Appendix Table 1. Brant Test of Parallel Regression Assumption

Variable	chi2	p>chi2	df
All	594.15	<0.001	46
Health Status			
Good	84.63	<0.001	2
Fair/Poor	95.01	<0.001	2
Uninsured	1.34	0.511	2
Post (Medicare)	1.98	0.372	2
Uninsured*Health Status			
Good	0.88	0.644	2
Fair/Poor	0.02	0.990	2
Post (Medicare)*Health Status			
Good	4.3	0.116	2
Fair/Poor	1.8	0.407	2
Uninsured*Post (Medicare)	*12.43*	*0.002*	*2*
Uninsured*Post (Medicare)*Health Status			
Good	3.66	0.161	2
Fair/Poor	3.54	0.170	2
Age	2.29	0.318	2
Age*Age	7.53	0.023	2
Male	28.38	<0.001	2
Race/Ethnicity			
Black	6.23	0.044	2
Hispanic	20.63	<0.001	2
Other Race	2.37	0.306	2
Education			
High School Graduate	14.43	0.001	2
Some College	15.37	<0.001	2
College Graduate	23.9	<0.001	2
Region			
Northeast	2.14	0.342	2
South	8.66	0.013	2
West	19.43	<0.001	2

Appendix Table 2. Results from Hosmer-Lemeshow Tests

Estimation Approach	
Health Status	p-value
Multinomial Logit	
E/VG	<0.001
Good	0.388
F/P	0.385
Dead	0.220
Ordered Logit	
E/VG	<0.001
Good	<0.001
F/P	<0.001
Dead	<0.001
Generalzied Order Logit	
E/VG	0.001
Good	0.483
F/P	0.056
Dead	0.548

Appendix Table 3. Measures of Fit for Alternative Estimation Approaches

	Mlogit	Ologit	Gologit
Log-Lik Full Model:	-15657	-15901	-15651
LR	8871	8383	8883
Prob > LR:	<0.001	<0.001	<.001
McFadden's Adj R2:	0.217	0.207	0.217
Cragg-Uhler(Nagelkerke) R2:	0.443	0.424	0.443
AIC*n:	31457	31853	31445
BIC':	-8197	-8158	-8209
AIC used by Stata:	31457	31853	31445

Table 4a. Coefficients from Ordered Logit

	Coefficient	P > |z|
Health Status		
Good	1.798	<0.001
Fair/Poor	3.606	<0.001
Uninsured	0.345	0.001
Post (Medicare)	-0.162	0.043
Uninsured*Health Status		
Good	-0.156	0.286
Fair/Poor	-0.394	0.007
Post (Medicare)*Health Status		
Good	-0.015	0.860
Fair/Poor	0.103	0.292
Uninsured*Post (Medicare)	-0.056	0.784
Uninsured*Post (Medicare)*Health Status		
Good	-0.081	0.754
Fair/Poor	-0.105	0.687
Age	0.053	<0.001
Age*Age	0.001	0.476
Male	0.163	<0.001
Race/Ethnicity		
Black	0.257	<0.001
Hispanic	0.159	0.017
Other Race	0.135	0.219
Education		
High School Graduate	-0.374	<0.001
Some College	-0.477	<0.001
College Graduate	-0.725	<0.001
Region		
Northeast	-0.049	0.324
South	0.070	0.085
West	-0.057	0.280
Constants		
Cut 1	0.541	
Cut 2	2.610	
Cut 3	5.494	

P-value of the X^2 Tests on the set of coefficients representing the following Null Hypotheses:

Hypothesis:	
Upre = Ipre	0.003
Upost = Ipost	0.003
Upre = Upost	0.153
Ipre = Ipost	0.074
(Upost - Upre) = (Ipost - Ipre)	0.627

Table 4b. Coefficients from Generalized Ordered Logit

	Good vs. Exc/VG		Fair/Poor vs. Exc/VG		Dead vs. Exc/VG	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Health Status						
Good	1.95	<0.001	1.363	<0.001	0.528	0.012
Fair/Poor	3.44	<0.001	3.494	<0.001	1.908	<0.001
Uninsured	0.31	0.003	0.419	0.013	0.635	0.074
			-0.043	0.755	-0.370	0.232
Post (Medicare)	-0.26	0.003	-0.146	0.484	-0.153	0.756
Uninsured*Health Status						
Good	-0.20	0.237	-0.146	0.484	-0.153	0.756
Fair/Poor	-0.42	0.081	-0.448	0.032	-0.500	0.220
Post (Medicare)*Health Status						
Good	-0.04	0.704	0.021	0.880	0.594	0.084
Fair/Poor	0.24	0.185	0.093	0.526	0.438	0.155
Uninsured*Post (Medicare)	-0.18	0.331	0.466	0.076	0.850	0.127
Uninsured*Post (Medicare)*Health Status						
Good	0.04	0.881	-0.628	0.056	-1.072	0.152
Fair/Poor	-0.21	0.604	-0.702	0.034	-0.782	0.220
Age	0.07	<0.001	0.034	0.034	0.011	0.715
Age*Age	0.00	0.295	0.002	0.404	-0.013	0.007
Male	0.11	0.005	0.194	<0.001	0.594	<0.001
Race/Ethnicity						
Black	0.29	<0.001	0.263	<0.001	0.078	0.533
Hispanic	0.32	0.001	0.098	0.272	-0.626	0.003
Other Race	0.34	0.021	-0.117	0.479	-0.373	0.306
Education						
High School Graduate	-0.36	<0.001	-0.489	<0.001	-0.028	0.823
Some College	-0.44	<0.001	-0.651	<0.001	-0.141	0.391
College Graduate	-0.70	<0.001	-0.913	<0.001	-0.264	0.148
Region						
Northeast	-0.07	0.234	-0.029	0.690	0.105	0.495
South	0.03	0.527	0.161	0.005	0.108	0.402
West	-0.18	0.004	0.171	0.023	0.042	0.799

P-value of the X^2 Tests on the set of coefficients representing the following Null Hypotheses:

Hypothesis:	**P-value**
Upre = Ipre	0.047
Upost = Ipost	<0.001
Upre = Upost	0.030
Ipre = Ipost	0.043
(Upost - Upre) = (Ipost - Ipre)	0.254

Appendix Table 5. Comparison of the Extrapolation from the Three Models

	U post at 71 - U at 65 [A]	U pre at 71 - U at 65 [B]	I post at 71 - I at 65 [C]	I pre at 71 - I at 65 [D]	ΔU [A] - [B] [E]	ΔI [C] - [D] [F]	Triple Dif [E] - [F] [G]
1. Base model with multinomial logit - one simulation							
Excellent/VG	-3.8%	-11.4%	-10.4%	-16.9%	7.6%	6.5%	1.1%
Good	-7.6%	-2.4%	-0.4%	5.7%	-5.2%	-6.1%	0.9%
Fair/Poor	-4.1%	1.1%	2.8%	3.7%	-5.2%	-0.9%	-4.3%
Dead	15.5%	12.7%	8.0%	7.5%	2.8%	0.5%	2.3%
2. Base model with ordered logit - one simulation							
Excellent/VG	-3.8%	-9.4%	-9.9%	-14.9%	5.6%	5.0%	0.6%
Good	-7.5%	-8.4%	0.1%	0.7%	0.9%	-0.6%	1.5%
Fair/Poor	-11.1%	-8.4%	1.6%	4.8%	-2.7%	-3.2%	0.5%
Dead	12.4%	16.2%	8.2%	9.4%	-3.8%	-1.2%	-2.5%
3. Base model with gologit2 - one simulation							
Excellent/VG	-4.7%	-11.6%	-10.3%	-16.5%	6.9%	6.2%	0.8%
Good	-8.9%	-2.5%	-0.8%	4.3%	-6.4%	-5.1%	-1.3%
Fair/Poor	-2.7%	0.8%	3.1%	4.5%	-3.5%	-1.4%	-2.1%
Dead	16.2%	13.3%	7.9%	7.7%	2.9%	0.2%	2.7%